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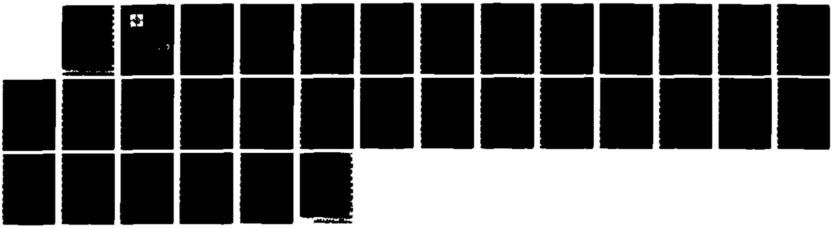

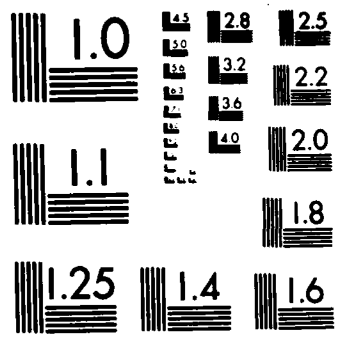

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Aiding Human Operators with State Estimates

James B. Roseborough
Thomas B. Sheridan

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Aiding Human Operators with State Estimates

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ABSTRACT

Three experiments are reported in which subjects must maintain a dynamic plant at or near some desired state by selecting actions based on a display of noisy state information and their own knowledge of the plant dynamic characteristics. In some cases, a normatively derived state estimate was displayed as an alternate information source, or decision aid. Results suggest that subjects are often able to simplify their own cognitive tasks significantly while degrading their overall task performance only slightly. Models of this cognitive behavior include: substituting an adequate stimulus-response like algorithm for one which requires maintenance of an internal state estimate; retaining point estimates of state when distributions over states are presented; partitioning the state space so that the model's state space has fewer states than than the actual process; and ignoring certain structural details of plant behavior which extend beyond analogical models assumed to be present in the subject. The implications for the design of decision aids based on state estimation are discussed.

1. INTRODUCTION

As controlled processes become larger and more complex, the operators must integrate larger amounts of available information into their own knowledge, or mental models. Computer aids may be necessary to help the operator deal with large amounts of available information quickly and effectively. This work will attempt to identify certain aspects of human cognitive behavior of interest to the designers of computer-based decision aids.

When the controlled process is dynamic, which by definition forces the pace of events, the operator may be under pressure to make decisions. Examples of controlled dynamic processes are power plants, other process control plants, ships, and airplanes. Adding to the operator's difficulty, if the system is in some abnormal state or a state unfamiliar to the operator, his models of the system may be partially or totally inaccurate.

There has been much written on the role of mental models in problem solving and decision making tasks [Stevens, 1980; Young 1983; Jagacinski, 1978; Young, 1981; Collins, 1977]. Early studies of the operator focused on continuous tracking tasks and later ones on the response to changes in plant dynamics [Niemela, 1975; Miller D.C, 1967]. The performance of subjects at prediction tasks has also been measured and modeled [Laios, 1978; van Bussel, 1980; van Heusdenn, 1980]. Some authors have studied qualitative reasoning about physical systems [Forbus, 1981; DeKleer, 1975]. Recently, there has been growing interest in modeling the cognitive aspects of the human operator [Rasmussen, 1976; Greenstein, 1982; Rouse, 1977].

There are many models of decision making available, some being prescriptive and others being descriptive in nature. The expected utility model for normative decision making is probably the least controversial prescriptive model of decision making, yet it is virtually impossible to implement in real applications [Sage, 1981]. It has been used as the basis for adaptive decision aids [Freedy, 1976]. There seems still to be a need for studying the relationship between the normative decision making models and descriptive decision making models.

1.1 GOALS OF RESEARCH

The goal of this work has been to examine the relationship between an operator's mental model and a computer based process model for some interesting but limited decision making context. The context which has been chosen for study is decision making in the the control of a stationary, dynamic process. By making this choice, the discussion of mental models and computer models is restricted to a manageable level. Additionally, there already exists a large amount of theoretical information about the automatic control of stationary dynamic processes. Effectively, this means that prescriptive models for decision making in this context are readily available.

There is now te choice between looking at a real process or remaining in the laboratory. Consider a couple of points which make the first alternative less desireable:

1) If there is no normative model of how the decisions should be made, then there is no way to measure the effectiveness of a proposed decision aid.

2) If there is a normative model of decision making which is both available and satisfactory (with respect to some accepted model of the process), then the sub-normative human should be replaced with a machine which implements the normative procedure and any proposed decision aids are unnecessary.

3) If a normative procedure exists with respect to a model of the process, there may be important differences between the model of the process and the actual process. The presence of these differences may be the reason for the human operator. However, these differences also make the procedure sub-normative with respect to the real process, so any proposed decision aid may not be evaluated in this situation.

Thus we have the simple choice of proposing decision aids for cases where their effectiveness may never be evaluated or they are unnecessary in the first place, or studying decision aids for artificially constructed processes in the laboratory where the results may be stated with some confidence, but the extrapolation to real systems is in question. We have chosen to remain in the laboratory where normative decision algorithms can be developed.

We must mention that there is not much hope of modeling a human perfectly. If an experimenter manages to predict every decision for a subject over a finite number of observations, then there is always the chance that the subject was responding to the particular sequence presented and a slight variation in the stimulus would produce a vastly different response from the subject. Ideally, the experimenter searches for a model which is simple yet successfully predicts the human's behavior for a large percentage of the time. It is always possible to attribute unpredicted human behavior to stochastic elements within the human, yet the basic idea behind modeling is to be able to view the human as comprised of deterministic rather than stochastic elements.

It is always possible to draw up a model with a large number of parameters such that our sequence of experiments results in precisely the observed set of responses. But such a model does not have the characteristics of simplicity or elegance, it would not generalize to other situations, and it would be of limited interest in any other setting. In modeling, we seek a balance between robust predictability and number of model parameters. Ultimately, the test of any model is to make predictions in a set of circumstances which have not been tried. We will do this with the models under development presently.

Regarding a descriptive model of the human, there is of course a great deal of literature about cognitive processes in general, some of it having direct relevance to our discussion. In the next section we will present a general process model involving probabilistic state transitions. The various studies of human probabilistic updating and prediction tasks [Laios, van Bussel, van Heusdenn] show that the human behaves differently from accepted normative descriptions. In an oversimplified way, what is meant by mental models versus computer models in decision making is: how it is done versus how it should be done.

2. SELECTION OF A REPRESENTATIVE TASK

As a limited set of problems for which the study of decision making is important, we have chosen the regulation of a stationary dynamic process with stochastic state transitions. The most basic model for this process is given by Figure 1. The process has a state which is dependent on actions taken by the operator but is not directly observable. By regulation is meant that there is some goal state at which the operator seeks to keep the process by means of his control actions. More precisely, there is some reward per unit time defined solely over the states of the process, and it is the goal of the operator to select his control actions so as to maximize the average rate at which the reward is collected, that average being taken over all time.

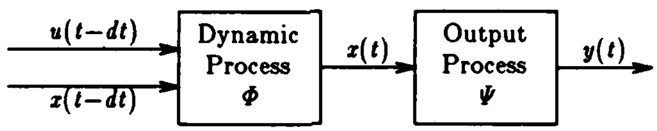


Figure 1. General Process Model.
The process consists of a dynamic process, Φ, and an output process, Ψ. The observable $y(t)$ is dependent only on the state $x(t)$ which in turn depends on the last state $x(t-dt)$ and the last control input $u(t-dt)$.

The stationary dynamic process with stochastic state transitions is a very general model and we choose to present it mathematically as,

$$P(x(t+dt)=x_i) = \sum_{j=1}^{n} \phi_{ij}(u(t))\, P(x(t)=x_j), \qquad i=1,n \tag{2.1}$$

$$P(y(t+dt)=y_i) = \sum_{j=1}^{n} \psi_{ij}\, P(x(t+dt)=x_j), \qquad i=1,m$$

where $x(t)$ is the process state at time t, $u(t)$ is the input at time t, $y(t)$ is the observable at time t, $P(a)$ is the probability of a, n is the number of states and m is the number of possible observables. The ϕ_{ij}'s and ψ_{ij}'s are process parameters, which are conditional probabilities among states and outputs:

$$\phi_{ij}(u_k) = P(\ x(t+dt)=x_i \mid x(t)=x_j,\ u(t)=u_k\ ) \tag{2.2}$$

$$\psi_{ij} = P(\ y(t)=y_i \mid x(t)=x_j\ )$$

Note that these parameters must conform to the usual constraints of a probability distribution (i.e. $\sum_i \phi_{ij}=1, j=1,n$; and $\sum_i \psi_{ij}=1, j=1,n$).

In the literature (2.1) is called a partially observable Markov model or an automata model and its

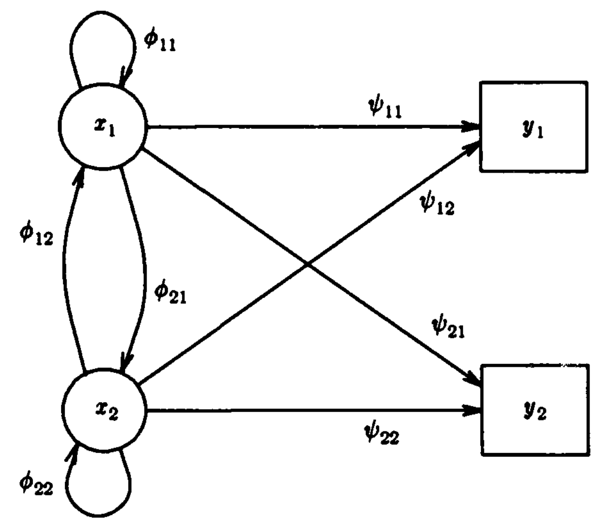


Figure 2. A simple Markov model with noisy outputs.
The ϕ_{ij} are transition probabilities among states while the ψ_{ij} are the probabilities of each output conditional on each state. The diagram indicates state transition behavior for only one input, say u_2.

control has been studied [Amram, 1982; Kakalick, 1976]. Figure 2 presents an example of a partially observable Markov model under the influence of a specific control alternative. Circles represent possible process states and boxes represent possible observations, sometimes called output tokens.

Conceivably, the behavior of any stationary dynamic process could be represented by the model given in (2.1). By having stochastic transitions, we do not exclude deterministic phenomena in which all state transition probabilities are either zero or one. Specification of the model does require enumeration of all states, outputs, and transition and output probabilities for the modeled process. In practice, of course, this cannot be done for processes with continuous states. Therefore, we must either study processes that have a small number of states or be satisfied with a relatively course discretization of a continuous process. Note that if such an enumeration of a continuous process could be done, then the distinction between linear and non-linear process dynamics would not be important. A linear process model such as $\dot{x} = \mathbf{A}x + \mathbf{B}u$ may be thought of as a shorthand representation of a large amount of state transition information.

The restriction that the process model is stationary means that the transition and output probabilities do not change in time. This does not prevent us from using the Markov model for situations in which failures occur that change the "characteristic" of certain process sub-components. It does mean that we cannot analyze the effects of unmodeled dynamics on our decision-making models. In spite of the enumeration problems described above, (2.1) serves as a useful parameterization of a set of models for which human decision making can be easily studied. Perhaps most importantly, it is possible to specify normative control behavior for this model and even calculate it when the number of states is small. This will be discussed in the next section.

3. NORMATIVE CONTROL OF THE MARKOV PROCESS

If a utility function is added to the general process model given by (1), then normative or prescriptive behavior may be determined. To study the regulation problem, a scalar valued reward function, $r(t)$, is defined over the states of the process as follows:

$$r(t) = \sum_i r_i \, P(x(t)=x_i) \tag{3.1}$$

The constant r_i represents the reward issued when the process is in state x_i for one time period. Reward and utility are used interchangeably in this discussion. The normative control action at time t for the process specified in (3.1) with the reward function specified in (3.1) is determined as follows. A belief vector, $f(t)$, is formed and updated after each input-observation pair. Each component, $f_i(t)$, represents the subjective probability that the process is in state x_i at time t. The belief vector components are updated according to two influences, that of the last control action and that of the present observation:

$$f_i^-(t) = \sum_j \phi_{ij}(u(t-dt)) \, f_j^+(t-dt) \tag{3.2}$$

which accounts for the expected process state transitions associated with the deterministic influence of the control input for each time step. Assuming output y_k is observed at time t, the state is updated according to a Bayesian update

$$f_i^+(t) = \frac{\psi_{ik} \, f_i^-(t)}{\sum_j \psi_{jk} \, f_i^- j(t)} \tag{3.3}$$

These two parts, the prediction and update processes, may be called the state estimate part of the normative control procedure.

Each action is then given a ranking according to how much reward can be expected to be derived from taking that action under the present belief. The action possessing the highest expected incremental reward is chosen. Letting $v_i(t)$ represent the expected incremental reward of taking action ui at time t. For the case where a stationary state transition matrix applies such as that in (1), and the reward function is constant and linear over the states as in (2), $v_i(t)$ is a linear function of constant weighting coefficients, w_{ij}. That is,

$$v_i(t) = \sum_j w_{ij} \, f_j(t) \tag{3.4}$$

For the special case given, the w_{ij} are determined off-line from evaluating an expected incremental utility algorithm using the plant model. If $v_i(t)$ is larger than all other $v_j(t)$, $j \neq i$, then action u_i should be chosen at time t.

The basic elements of the normative control procedure are shown in Figure 3. What is important to note is that the the belief state $f(t)$ consists of a probability (or likelihood) associated with each state of the process and each of these probabilities is used in a precise way to determine the present action as well as the probabilities after an additional observation is made.

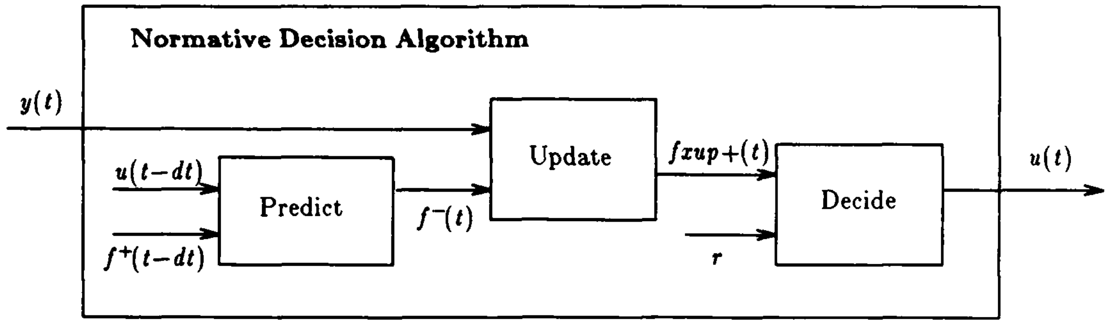


Figure 3. Elements of the Normative Decision Algorithm.
The belief state, consisting of a distribution over the all states of the process is an essential part of the normative model of decision making for the experimental task.

Note that if a system had a unique symbolic representation of each possible belief state, and it "branched" from symbol to symbol correctly for all possible process output tokens, that system would be executing a normative decision algorithm. This hypothetical example may well be how experts control a process. Due to vast experience, almost every process state which they encounter they seem to recognize and may have a unique verbal label for. Thus they have a unique symbolic representation for each state of the process. Feeling they know what state the process is in, they may also know what outputs indicate movement to what other states. That is, they have well calibrated branching rules among process states.

It is not necessary to have a computer working exactly as outlined to produce normative behavior. Anything which produces identical input-output behavior the same decision making behavior as the normative algorithm may be considered a normative decision maker, regardless of the details of it's internal mechanics. Indeed the normative decision making algorithm is itself a finite state automaton, and numerical representations of belief sates within the computer may be considered to be enumerated symbols for each possible belief state.

3.1 PROPOSED DECISION AID - A NORMATIVE STATE ESTIMATOR

In the previous section, the components of a normative algorithm for decision making in the context of controlling a stationary dynamic process were outlined. These may serve as a reference for descriptive models or basis for normative models of the human decision maker. We assume that the human implements some algorithm when he selects actions based on observations, and this algorithm consists of parts possibly including a prediction part, an updating part, and a decision rule part. These parts, though similar in function to their counterparts in the normative algorithm, differ in significant ways and it is these differences which give rise to the sub-normative behavior of the human decision maker.

A proposal for a decision aid is to provide a normatively derived state estimate to the operator that he can use to augment his own sub-normative state estimate. Presumably, the decision maker's internal state estimate when the aid is present will be "closer" to the normative state estimate than that which he forms in the unaided case, and the decisions which are made will be better in an expected value sense. The first experiments were designed to show that a decision aid based on providing normative estimates of process state could be of use to human decision makers. The next sections will describe the experimental task that was chosen and some results.

4. EXPERIMENT ONE - A THREE STATE TRACKING TASK

In order to evaluate the usefulness of a normative state estimate as a decision aid, and to study human decision making in a controlled environment, a simple partially observable Markov process was constructed with three states, three outputs, and two control actions. The process parameters were chosen so that the overall task had the characteristics of a single degree of freedom, first order tracking experiment where the plant was slightly non-deterministic and the observations were noisy. The exact process parameters which were used are given in Appendix 1.

The subject sat in front of a computer generated display which displayed one of three possible output tokens at the beginning of each timestep. He was instructed that these tokens gave an indication of the state of an invisible process, and he was given the parameters of the process in the form of a state-transition diagram. The condition where the output tokens were the sole indication of state available to the subject was termed the "raw observables" condition since it corresponded to the information normally present in an unaided process control situation.

In terms of the model outlined in Section 2, the output token is the $y(t)$ which takes on some value y_i, and the invisible state of the process is $x(t)$ which presumably has some value x_j at each time.

The subject responded to displayed information by moving a toggle switch in one direction or the other according to the action he thought would maximize his incremental score received during a trial. One position of the switch corresponded to movement of the state in one direction, while putting the switch in the other direction corresponded to movement of the state in the other direction. The time remaining to make the decision as well as the decision being made were also displayed on the screen. At the end of a trial, the total score received by the subjects was displayed.

In other conditions, a normative estimate of the state of the process was displayed alongside the raw observable. This was presented in the form of a bar graph, with the length of each bar corresponding to the estimated probability of the process being in the corresponding state. The normatively derived state information was termed "processed data." In some trials only the processed data was presented, and in others it was presented together with the raw observable.

Subjects were graduate students in mechanical engineering, all familiar with the principles of control systems. Before each trial within a condition, training trials were given in that condition until the subject felt comfortable. Typically, the experiment lasted approximately two and one half hours, with roughly forty percent of the time spent in training by the subject.

Subjects were given all of the process parameters as numbers at the beginning of the experiment though no attempt was made to provide them with a rich understanding of the qualitative process characteristics. Each trial consisted of 120 decisions, spaced at intervals ranging from 0.25 seconds to 2.0 seconds per decision but constant during each trial. Each process output presented to the subject and the resulting decision made by the subject (the toggle position at the end of a timestep) were recorded for later analysis.

Four parameters of the experiment varied for each trial. These were, process uncertainty, output uncertainty, process rate, and presence/absence of the decision aid. A large process uncertainty, denoted E_p for entropy of the process, corresponds to cases where transition probabilities were not near zero or one. Hence knowledge of the present state for a process with a large process uncertainty does not have much implication on knowledge of future states. The channel uncertainty is denoted E_c and indirectly describes how much information about the plant state is given by a single observation.

Parameter	Value	Subject 1 Mean	Subject 1 StDev	Subject 2 Mean	Subject 2 StDev	Subject 3 Mean	Subject 3 StDev	F Samp	F Crit
Observer	No	48.5	13.6	45.5	10.4	40.6	9.3	7.78*	6.85
	Yes	51.7	10.8	47.8	12.4	46.6	12.8		
Plant	0.187	53.7	20.1	52.2	14.0	42.0	12.3	6.27*	4.79
Entropy	0.333	45.7	9.1	43.3	3.3	39.5	8.6		
	0.418	46.2	5.2	40.3	5.7	40.3	5.7		
Channel	0.131	53.9	7.8					3.79	3.95
Entropy	0.391	47.8	14.7	45.4	9.9	40.4	9.5		
	0.651	48.0	10.9	47.2	12.7	41.7	10.0		
	0.911	44.5	17.4	43.6	7.5	39.7	8.3		
Process	0.133	43.9	4.7	41.6	6.7	44.1	6.1	2.61	3.48
Rate	0.267	43.6	13.4	38.8	5.3	40.1	6.8		
	0.533	55.0	17.9	48.6	10.6	41.4	11.7		
	1.067	51.7	11.0	50.9	11.8	36.8	10.1		
	2.117			47.0	9.8				

TABLE 1. Summary of Results for First Experiment.
A (*) indicates that the null hypothesis - decision performance is independent of the parameter value - is rejected at the 0.99 level.

The experimental test matrix and the raw results for each trial and subject are given in Appendix 2. The summary results of this first experiment are presented in Table 1. The score presented is calculated by taking the components of the Bayesian state estimates of process state at each time step and summing them over the trial, and then dividing by the number of decisions per trial. By this method an estimate of the long-term average score for the subject and condition is calculated. The results indicate that the normatively derived state information aided decision performance, but it may be surprising how slight this effect is. The null hypothesis, "The computer aid does not improve decision making performance" was tested, and was rejected with an F-statistic of 7.78 which is significant at the 0.99 level.

4.1 THE USE OF SIMPLIFIED, "THOUGHTLESS" CONTROL ALGORITHMS

The inputs selected and outputs observed up until time t-dt may be fed into any model of the human in order to predict his action selected at time t. Five different models of the human decision maker were examined corresponding roughly to the normative model degraded in various ways. The models which were used were arrived at by examining protocols of subjects.

Model 1 consisted of a normative state estimator with a normative decision rule. Model 2 consisted of a normative state estimator with a "truncated state" decision rule (discussed below). Model 3 consisted of a "decaying memory" state estimator (discussed below) with a normative decision rule. Model 4 consisted of a decaying memory state estimator with a truncated state decision rule. Finally, Model 5 was a direct input→output mapping model or stimulus→response model, in which the human does not hold any belief state from decision to decision but merely responds to the current observation according to some lookup table which he has derived either from structural knowledge about the task or sufficient experience.

The normative state estimator and normative decision rule were taken directly from the normative decision making algorithm presented earlier.

The truncated state decision rule was a model in which the state estimate of the process held by the human is first truncated to be one of three statements: 1) the process is in state x_1, 2) the process is in state x_2, or 3) the process is in state x_3. The truncation was made according to which probability in the belief state was the highest; If $f_1 > f_2$ and $f_1 > f_3$ then statement (1) was used. The action was then selected according to this belief, conceptually speaking from a lookup-table where each of the three statements will result in a specific action. The lookup table used in the model was: $x_1 \rightarrow u_2$ chosen; $x_3 \rightarrow u_1$ chosen; $x_2 \rightarrow u(t-dt)$ chosen.

The decaying memory state estimator was a model in which previous observations were combined with weighting factors that decay exponentially as the observation was made further and further in the past. This corresponded to ordinary first order filtering of the observations to arrive at a belief state. By examining the predictive capability of models with various decay rates, a good model was found to be when the decay rate was set to 0.2 seconds.

Table 1 presents the results of comparing each model of the human with actual decisions made for each subject. From these data, it is quite clear that of the five models examined and for this experimental task, the ideal Bayesian or normative model is not a good predictor of human decision making behavior. This is in agreement with much of the literature which has discovered that people do not combine new observations with probabilistic statements in a Bayesian way. Of the remaining four models, none is significantly more predictive than the others. Subjects' protocols indicated that they were using something like the stimulus response model. It should be emphasized that although the stimulus response model is a good descriptive model of the subjects' behavior, it is a bad prescriptive model. More will be said about this point later.

Model Number	Model Name	State Estimate	Control Rule	Subject Number 1	2	3
1	Simple	-	-	81.0	72.7	62.4
2	Optimal Bayesian	Bayesian	Optimal	59.8	51.9	56.3
3	Truncated Bayesian	Bayesian	Truncated State	82.5	76.3	65.3
4	Optimal Iconic	Iconic Memory	Optimal	80.4	70.4	61.3
5	Truncated Iconic	Iconic Memory	Truncated State	81.0	73.5	63.1

TABLE 2. Comparison of Predicted Actions to Recorded Actions. Entries are percentage of decisions where decision predicted by model matched decision made by subject.

5. EXPERIMENT TWO - TRAPPING WITH NEGATIVE EVIDENCE OF STATE

In the first experiment we observed that people can adopt a simple rote procedure for selecting actions in place of a detailed normative algorithm when they feel their interests are served by such a substitution. In certain real conditions, this type of response may be encouraged. For example, procedural handbooks in power plant control rooms or military command and control systems both promote the "trained monkey" type of stimulus->response behavior from operators. Though this type of behavior may be desirable in some circumstances, this work seeks to describe behavior where the cognitive activities play a larger role than simple translation of inputs into outputs.

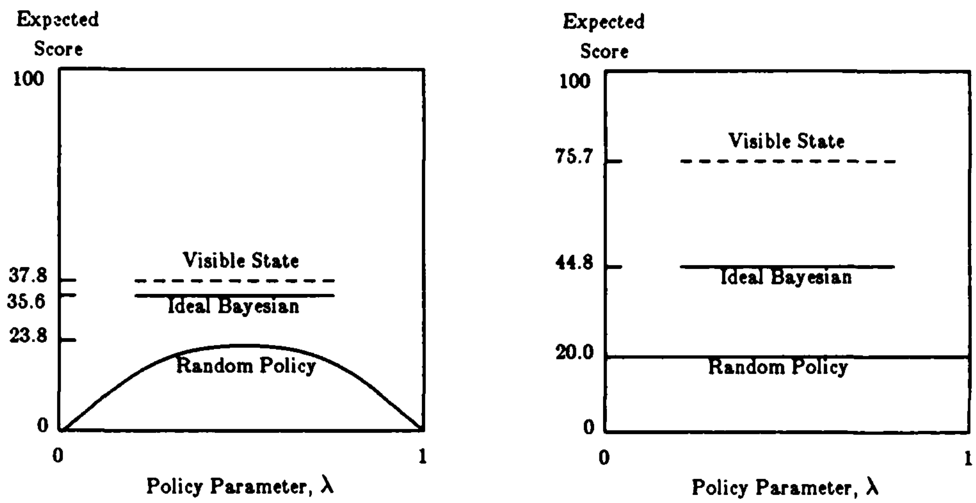
Modifications to the experimental parameters were sought which would make it difficult for subjects to apply simple rote procedures. Since the output matrix in the first experiment tracks the state of the process, it was easy for the subject to adopt a simple state estimation method such as: use the output token as the state of the process (believe whatever the output says). It was decided that using an output matrix such that the observables gave negative evidence of state would force the subject to hold a state estimate which was independent of the momentary "state" of the output token.

With the process parameters used in the first experiment, it was difficult for the experimenters to distinguish good human decision making behavior from a random policy. A random policy is one where the action at each time step is chosen from a constant distribution, regardless of the state information that has passed before the decision maker. With two actions available at each timestep, the possible random policies may be parameterized by a single variable λ, the probability of taking action u_1. The theoretical average score under that policy may then be determined analytically. Doing so shows that the experiment chosen provides little difference between the score of a "good" random decision maker ($\lambda = 0.5$) and a normative decision maker. The process parameters for the second experiment were chosen to increase the differences between normative, or knowledgeable, behavior and random policies.

In Figure 4(a), the expected scores for three different decision makers are presented. The top line is the score that would be achieved if full knowledge of the state were available. The state transition matrix determines where this expected score will be in comparison to the reward achieved in the goal state. The second line is the expected score of a normative decision maker, and the bottom line is that for the random policy, shown for various values of the parameter λ. In Figure 4(b), we see the corresponding plot for the second experiment showing a larger difference between the normative and chance policies.

The second experiment may be described qualitatively as follows: Under one action the state of the process changes wildly. Under the other action the process stays in the same state for long periods. The goal of the operator is to "capture" the process in the goal state and keep the process there as often and as long as possible. With the parameters chosen, any random decision policy will produce the same average score of twenty percent of the time spent in the goal state, while the normative control will average approximately forty-four percent.

The conditions of the experiment were the same as those of the first experiment with the following exception. The decision time was held constant throughout the experiment at 1.0 seconds. Also, the subjects worked with four separate conditions: 1) State of process directly observable, 2) Only output token displayed, 3) Output token plus decision aid, and 4) Decision aid only.



(a) Experiment 1

(b) Experiment 2

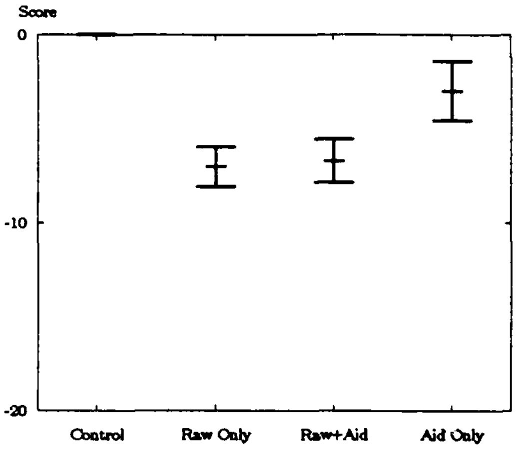
Figure 4. Expected Scores for Various Decision Makers.
The expected scores for various random and intelligent decision policies calculated for the process parameters used in the first and second experiment.

5.1 THE REJECTION OF SOUND ADVICE DUE TO INFORMATION OVERLOAD

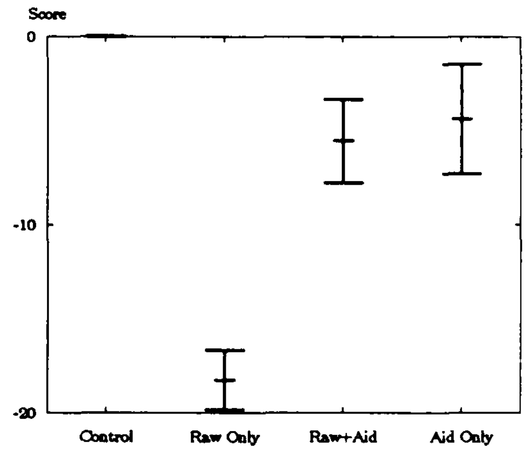
Figure 6 presents results for two subjects which were somewhat typical. The condition when the state is displayed, marked "control," established a base level of errors for the subject. The condition when only raw observable information was presented is marked "raw only," and was the hardest for all subjects. For some trials, only the aid was presented, and all subjects achieved better scores under this condition. For the condition when both raw information and processed information were available, some subjects seemed to use the aid while others seemed to ignore it, judging by the scores which were received.

It is interesting that those subjects whose scores seemed to reflect use of the aid whenever available also claimed they used the aid. They believed they could not do any better than the aid while the others believed their own methods of state estimation were superior to that provided as an aid. This is in spite of the fact that all subjects were told the aid performed the state estimation calculations correctly. Those that chose not to use the aid also complained that the additional information was confusing and too much too handle.

This reinforces an important issue being raised by this work - when is more information (in the form of an aid etc.) too much for the operator to deal with? It has been shown that the amount of information which a human may remember in making absolute judgements with respect to one-dimensional stimuli is seven items, plus or minus two [Miller, 1967]. So how do we, as plant engineers and scientists, expect the operator to deal with several hundred observable items at a time? In the first experiment, we saw that the subjects adopted a simple input→output rule instead of an elaborate normative procedure. This was largely a matter of convenience, but even though the second experiment is small in number of states and observables, it is already almost necessary for the subjects to perform some simplifications on the incoming data to process it at all. The nature of these simplifications is what will be explored in the remainder of this paper.



Results Summary for Subject Two



Results Summary for Subject Four

Figure 5. Results Summary for Two Subjects in the Second Experiment. Subject two apparently did not use normatively derived state information when raw information was also available, though his performance was improved when only processed information was available. Subject four seemed to use processed information whenever it was available.

5.2 PARTITIONING, POINT ESTIMATES, AND FOCUS

From the second experiment, it appeared that subjects did use an explicit state representation; many referred specifically to one in their own descriptions of "what they were doing." From some of these statements, three ways in which the subjects appear to simplify their own cognitive workload without incurring a severe penalty in performance have been developed. We will call these partitioning, point estimates, and focus.

Partitioning is a method of representation simplification in which the number of possible values which a state variable may take on in the representation is smaller than the number of values the state variable may take on in the actual system. "Number of values in the actual system" refers to an approximate notion of the number which system designers or well-informed operators would consider the state variable to be able to take on. An example of partitioning is when a state variable which is continuous, having infinite states, is represented as having only a few possible values, say "high," "medium," and "low."

As a physical example, suppose the process under study is an automobile engine and the state variable of interest is the level of oil in the engine. A normative state estimate would assign a probability to each possible level of oil. It may well be that the person only distinguishes between full, low, and empty - a partitioned state variable. A belief state on the partitioned state space would assign probabilities to each of the three represented values, P(full), P(low), P(empty).

The fuzzy set approach to modeling or control implicitly incorporates this type of simplification. When fuzzy set membership functions are drawn for "tall men" vs. "short men" and actions are selected on the basis of membership values in such sets, then all subtle variations in height have been ignored except for the fact that an item has a varying degree of membership in one set or another.

Point estimates of state are used to simplify the representation of a state estimate from a distribution over a set of points to the belief in a single point as "the" state of the process. This method of thought pervades failure analysis where great efforts are put into finding "the" cause of failure. In a failure analysis situation. A normative decision maker would determine a probability for each of the failure modes (states) which he has modeled and act based on this distribution.

Though the point-estimate type of simplification may seem like a harmless or natural simplification to make, it can lead to very poor decision making behavior even in static decision environments. When a probability distribution is simplified to a point estimate, it is equivalent to assigning the probability of one of the states equal to one and the probability of all other states equal to zero. Thus the resulting decision algorithm is insensitive to the probability of almost every state. When the probability of a high-cost state is abnormally high though not the highest, the simplified decision algorithm will not account for this.

Focus occurs when some state variables of the process are ignored or the joint probability distribution is not taken in full detail. So-called common mode failures may not be considered by someone who focuses on one or a few state variables at a time. It is not clear exactly how this type of simplification will affect decision making performance in general.

6. EXPERIMENT THREE - APPROXIMATION TO A CONTINUOUS TASK

A third experiment has been constructed for the purposes of producing an explicit model of the human's decision algorithm in a specific decision making environment. The approach in this experiment has been to 1) construct a process with a much larger number of states than the previous experiments 2) record decisions made by subjects in response to process observables and 3) compare subjects' decisions to predictions made by various explicit models of the human. The explicit models of the human were based on the results of the previous experiments and analysis.

The process was given state transition behavior so that it behaved roughly as if it had two state variables, position and velocity, and a force input. The process had eighty-one states providing for nine levels of position and nine levels of velocity. Thus the process approximated a continuous process. The transitions were chosen so that the state behaved as if it were a particle bouncing between two walls, with some stochastic nature. The output took on one of eighty-one values at each timestep, and the output probabilities were chosen so that the euclidean distance between the state and the output in the (position, velocity) state space was approximately normally distributed. The reward was a maximum for the position of the particle in the middle, and decreased linearly as the position increased or decreased away from the middle state. Appendix 3 contains the precise state transition, output probability, and reward information.

Previously, the human's decision algorithm was broken down into two separate processes: a state estimation process and a decision rule process. There are also the reward function and belief state which are considered to be inputs or outputs of processes. The state estimate process, the decision rule process, and the reward function are assumed here to be stationary over the course of the experiment, while the belief state is assumed to be transient and changes from decision to decision as the human takes observations and his own actions into account. All four components are assumed to exist in the human decision making algorithm. We will focus on forming successful models of the three stationary components: the state estimator, the decision rule, and the reward function.

As models of the state estimation process, we have already presented several ways in which the human may simplify a state representation before using it in a decision rule process. Hence various combinations of these simplifications will result in several models of the state estimation process. Six models were used in this experiment. The models were not meant to be exhaustive or complete, but rather representative of the wide range of models which can be produced by such a reticulation.

The normative belief state for this process would be a set of eighty-one probabilities, one for each state. Figure 6 shows six displays which represent a normative belief state which has been simplified in various ways (those used in the experiment).

In addition to using various models of the state estimation process, two different models of the decision rule and three different models of the reward function were used. As we have said, the human should be applying the expected average incremental reward algorithm by looking at the consequences of each possible action infinitely far into the future. This is one model of the human decision rule. The other model is when the human considers the results of his action only for the next time step. These two models may be called long range versus short sighted decision making. The three reward function models used correspond to 1) that which is given, 2) one in which the task is essentially to avoid states far from the target state, and 3) one in which the task becomes to get in the target state as often as possible. These are diagrammed in Figure 7.

The results of applying this method of algorithm identification are summarized for one subject in

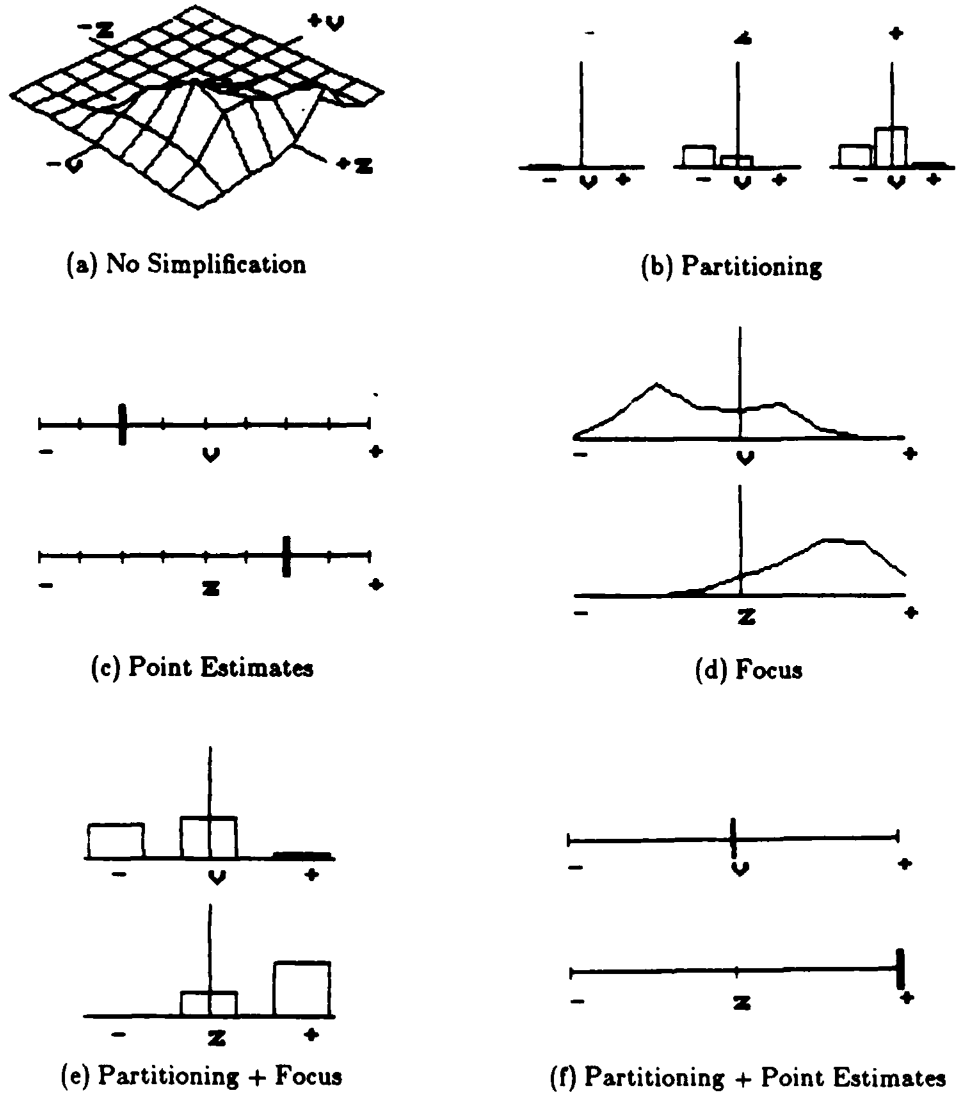
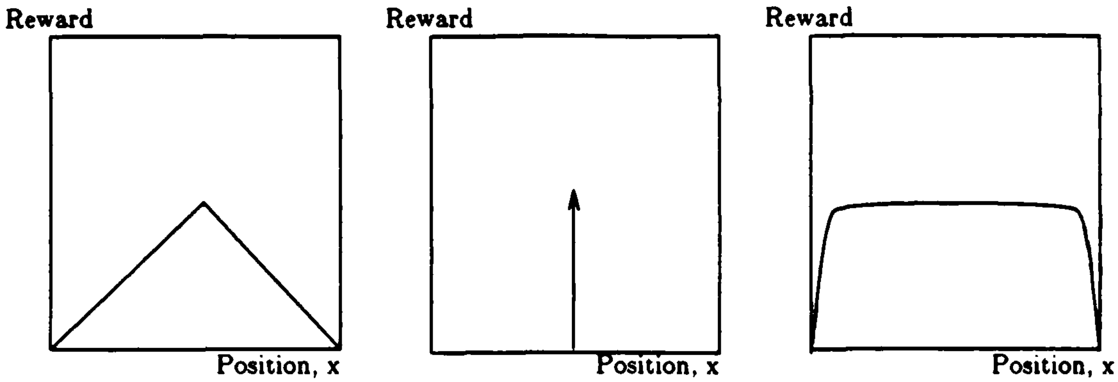


Figure 6. Various Displays Used in Third Experiment
Belief state representations may be simplified in various ways. These six ways were used as possible models of the human's state estimation process in dynamic decision making.

Table 3. There we can see that none of the models stands out as being highly predictive of the decisions made by the subject, though we could interpret this as meaning that the human uses such a simplified estimate that we are unable to observe any differences. Note however that when the results are grouped by decision rule, the results are much more predictive for the short-sighted reward function.

In accordance with these findings, an ad hoc model of one particular human subject was developed which combines the simplest state estimation model with a very simple lookup table (in our case



(a) Given Reward Function (b) Important Target State (c) Avoid Distant States

Figure 7. Models of the Subjects Internal Reward Function. These correspond to (a) given reward function, (b) avoiding states far from target state, and (c) hitting target as much as possible.

	Decision Rule #1			Decision Rule #2		
Model Number	Util Func #1	Util Func #2	Util Func #3	Util Func #1	Util Func #2	Util Func #3
0	42.5	43.6	41.7	40.6	41.4	41.1
1	51.1	51.9	50.3	49.4	57.2	55.6
2	42.2	43.6	39.7	40.6	40.8	40.8
3	50.8	51.9	50.0	48.6	57.2	55.6
4	38.0	37.8	39.2	37.2	21.9	41.1
5	51.7	52.5	50.8	49.1	57.2	55.6

TABLE 3. Predictability of Various Models in Third Experiment. Scores are in percentages of decisions which were correctly predicted by indicated models.

derived from experimental data). The use of this model to predict the human's actions is summarized in Table 4. There we see that an overall predictability of 69% is achieved compared to a maximum predictability of 57% using the other decision rules.

One explanation of these results could be the following. The human subject took the verbal instructions and immediately formed a decision rule such as that given by the histogram. In fact, under condition 0 this subject said he would look at what quadrant the peak was in, and act based on this result. His histogram data tend to support this. Figure 8 is a histogram of a point estimate of state, indexed on each of the three actions. Figure 9 presentwhat a the histogram for the normative algorithm would look like.

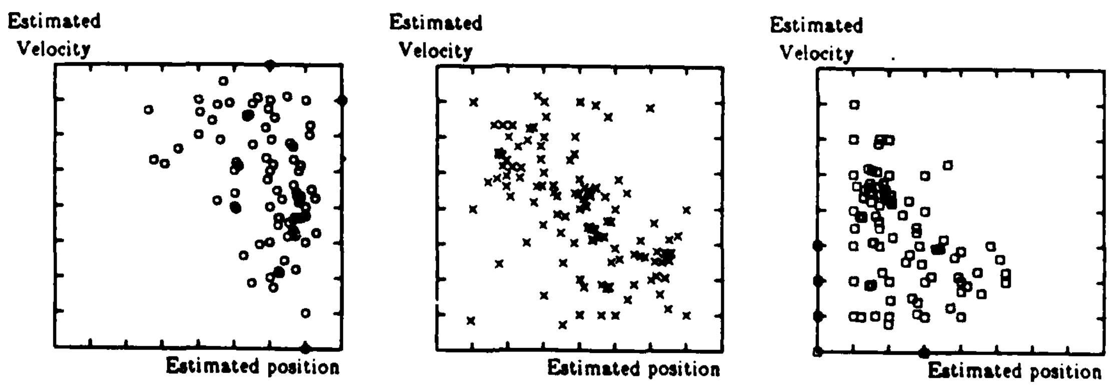
What is interesting is that the subject's histogram is exactly that which would be produced by a

Experimental Condition	Predictability (percent)
0	63.3
1	75.0
2	76.7
3	81.7
4	73.3
5	73.3
Overall:	69.4

TABLE 4. Predictive Capabilities of Ad Hoc Model.
Scores tabulated by experimental condition.

"good" decision maker for a similar task without bouncing walls, without the stochastic parts of the process, and for "average" process parameters given the rest of the process structure. It seems that the subject may be relating the task description to something with which he is familiar, then forming a decision rule lookup table from this.

Since the true test of any model is its ability to predict in unknown circumstances, the following experiment is suggested. If the person is merely relating the task description to some internal, archetypical task and choosing a decision rule based on this, then his histogram should be constant regardless of the exact task description given (at least until experience shows him that his model is poor). Therefore, give subjects widely varying task descriptions and apply the identification techniques developed to produce histograms. This model of the human would predict that despite variations in the process description, the subjects would all produce roughly the same action histogram. This should be the approach in further experiments.



Action u_1 taken   Action u_2 taken   Action u_3 taken

Figure 8. Summary of Actions Taken by Subject.
The values of hypothesized internal belief state variables are indexed on the action which was taken.

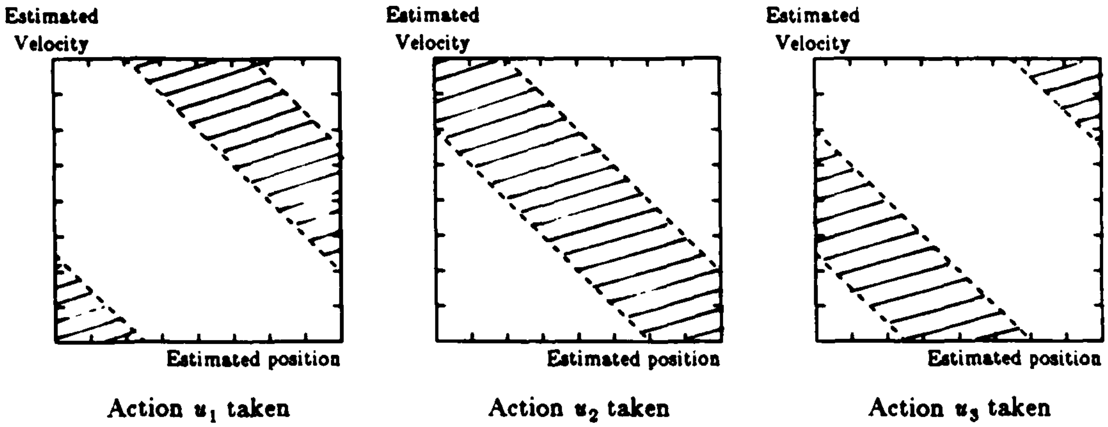


Figure 9. Approximate Histogram of Normative Decision Maker.
If the decision maker takes into account the bouncy walls of the process, the corners of the action histogram differ considerably from those produced by subjects.

7. CONCLUSIONS

A variety of modeling methods have been employed in attempts to converge upon a description of a human's mental model. To this end, a general class of experimental tasks was chosen (which can apply to a wide variety of real tasks) which consists of regulating a dynamic process having both deterministic and stochastic state transitions. The partially observable Markov model is an appealing model to use in such experimental settings because it is general yet tractable. Despite the ease with which a normative decision algorithm may be specified for this type of process, the implementation of a normative algorithm becomes extremely difficult or impossible as the process considered has more states.

Three experiments were reported in which the human apparently simplified his own mental task greatly without sacrificing much in terms of overall task performance. In the first experiment, the subjects appeared to simplify state estimation out of the experiment and perform a simple (and fairly successful) input→output translation. In the second experiment, evidence showed additional ways that the subject could simplify his internal state estimate to reduce his mental workload, yet his decision performance was not substantially diminished. In the third experiment, the human appeared to use a simple lookup-table on a simplified belief state instead of the complex decision-rule-applied-to- belief-state-and-reward-function which is suggested by normative models, and his performance again was relatively good. There is also evidence that this mapping is formed at the outset from structural descriptions of the experiment rather than during experimental trials where a process model is gradually changed based on empirical evidence.

8. APPENDIX 1 - PROCESS PARAMETERS FOR FIRST EXPERIMENTAL TASK

$$\Phi(u_1) = \begin{bmatrix} p_1 & 0 & 0 \\ 1-p_1 & p_2 & 0 \\ 0 & 1-p_2 & 1 \end{bmatrix}$$

$$\Phi(u_2) = \begin{bmatrix} 1 & 1-p_2 & 0 \\ 0 & p_2 & 1-p_1 \\ 0 & 0 & p_1 \end{bmatrix}$$

$$\Psi = \begin{bmatrix} q & (1-q)/2 & (1-q)/2 \\ (1-q)/2 & q & (1-q)/2 \\ (1-q)/2 & (1-q)/2 & q \end{bmatrix}$$

$$R = \begin{bmatrix} 0.0 & 1.0 & 0.0 \end{bmatrix}$$

Values for "p" used in experiment:

p	E_p
0.0574	0.187
0.1599	0.333
0.3707	0.418

Values for "q" used in experiment:

q	E_q
0.9741	0.131
0.8938	0.391
0.7764	0.651
0.5896	0.911

Expected scores for various decision makers:

DM with knowledge of state:		37.8 %
Normative decision procedure:		35.6 %
Random policy with λ =	0.0	0.0 %
	0.1	6.4 %
	0.2	12.8 %
	0.3	18.5 %
	0.4	22.4 %
	0.5	23.8 %
	0.6	22.4 %
	0.7	18.5 %
	0.8	12.8 %
	0.9	6.4 %
	1.0	0.0 %

9. APPENDIX 2 - RAW SCORES BY SUBJECT FOR EXPERIMENT ONE

Scores indicate percentage of time spent in target state.

Observer	E_p	E_c	Rate	Subject Number		
			(sec)	1	2	3
No	0.187	0.131	0.133	54.2		
			0.267	57.5		
			0.533	70.0		
			1.067	60.0		
		0.391	0.133	40.0		52.5
			0.267	22.5	46.7	28.5
			0.533	87.0	40.0	24.0
			1.067	36.0	76.0	23.0
			2.117		40.0	
		0.651	0.133	42.2	48.2	48.7
			0.267	57.5	29.0	44.0
			0.533	70.0	74.0	65.3
			1.067	60.0	68.0	41.0
			2.117		63.0	
		0.911	0.133	40.0	46.7	54.7
			0.267	12.0	40.0	38.5
			0.533	87.0	59.3	36.0
			1.067	64.0	48.0	48.0
	0.333	0.131	0.133	46.2		
			0.267	52.5		
			0.533	43.0		
			1.067	64.0		
		0.391	0.133	45.2		41.5
			0.267	56.5	42.2	48.5
			0.533	50.0	41.5	40.0
			1.067	56.0	44.0	49.0
			2.111		38.0	
		0.651	0.133	50.7	45.0	40.7
			0.267	43.5	44.5	44.0
			0.533	39.0	46.0	27.3
			1.067	26.0	41.0	30.0
		0.911	0.133	42.0	45.0	42.2
			0.267	40.0	37.5	44.5
			0.533	32.0	44.7	46.0
			1.067	44.0	50.0	20.0
	0.418	0.131	0.133	42.2		
			0.267	52.0		
			0.533	51.0		
			1.067	54.0		
		0.391	0.133	42.7		41.5
			0.267	45.5	36.0	45.0
			0.533	44.0	46.5	45.3
			1.067	48.0	47.3	46.0

			2.111		47.0	
		0.651	0.133	45.0	34.2	40.2
			0.267	43.0	40.5	28.5
			0.533	45.0	39.3	50.0
			1.067	54.0	41.0	40.0
		0.911	0.133	36.0	30.5	35.0
			0.267	41.0	32.5	39.0
			0.533	42.0	46.0	38.7
			1.067	54.0	43.0	34.0
Yes	0.187	0.131	0.133	61.0		
			0.267	74.0		
			0.533	41.0		
			1.067	76.0		
		0.391	0.133	46.7		30.7
			0.267	70.0	69.2	60.5
			0.533	53.0	57.5	68.7
			1.067	60.0	70.7	59.0
			2.111		68.0	
		0.651	0.133	69.5	65.7	44.2
			0.267	74.0	53.5	60.5
			0.533	41.0	49.3	63.3
			1.067	76.0	36.7	56.0
			2.111		56.0	
		0.911	0.133	56.0	53.7	47.5
			0.267	70.0	25.5	13.5
			0.533	57.0	55.3	64.0
			1.067	40.0	8.0	87.0
	0.333	0.131	0.133	45.7		
			0.267	48.5		
			0.533	45.0		
			1.067	46.0		
		0.391	0.133	50.5		40.7
			0.267	44.5	58.5	50.0
			0.533	46.0	53.5	42.7
			1.067	58.0	52.7	56.0
			2.111		45.0	
		0.651	0.133	46.0	34.0	39.5
			0.267	49.0	44.0	53.5
			0.533	45.0	40.7	52.7
			1.067	54.0	55.0	46.0
		0.911	0.133	54.5	43.7	38.7
			0.267	62.5	57.0	46.0
			0.533	48.0	34.7	46.0
			1.067	42.0	59.0	41.0
	0.418	0.131	0.133	45.5		
			0.267	43.5		
			0.533	55.0		
			1.067	54.0		
		0.391	0.133	38.5		41.5
			0.267	49.5	40.2	36.0
			0.533	44.0	48.5	43.3

	1.067	52.0	46.0	47.0
	2.111		41.0	
0.651	0.133	44.2	41.2	40.0
	0.267	45.5	44.0	32.5
	0.533	45.0	42.0	36.7
	1.067	56.0	58.0	38.0
0.911	0.133	40.7	32.5	33.7
	0.267	48.0	41.5	42.5
	0.533	39.0	44.7	37.3
	1.067	30.0	41.0	40.0

10. APPENDIX 3 - PROCESS PARAMETERS FOR SECOND EXPERIMENTAL TASK

$$\Phi(u_1) = \begin{bmatrix} 0.96 & 0.04 & 0.02 \\ 0.02 & 0.92 & 0.02 \\ 0.02 & 0.04 & 0.96 \end{bmatrix}$$

$$\Phi(u_2) = \begin{bmatrix} 0.50 & 0.50 & 0.25 \\ 0.25 & 0.00 & 0.25 \\ 0.25 & 0.50 & 0.50 \end{bmatrix}$$

$$\Psi = \begin{bmatrix} 0.10 & 0.45 & 0.45 \\ 0.45 & 0.10 & 0.45 \\ 0.45 & 0.45 & 0.10 \end{bmatrix}$$

$$R = \begin{bmatrix} 0.0 & 1.0 & 0.0 \end{bmatrix}$$

Expected scores for various decision makers:

DM with knowledge of state:	75.7 %
Normative decision procedure:	44.8 %
Any random policy:	20.0 %

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